Downlink Scheduler Optimization in High-Speed Downlink Packet Access Networks

Hussein Al-Zubaidy, Ioannis Lambadaris and Jerome Talim

Email: {hussein,ioannis,jtalim}@sce.carleton.ca; Systems and Computer Engineering, Carleton University, Ottawa, CANADA

Abstract

In this poster, we present some of our recent work and results. An analytic model and methodology were developed to determine *optimal scheduling policy* that involves two dimension space allocation: time and code, in High Speed Downlink Packet Access (HSDPA) system. The optimal policy is the policy that yields the maximum system throughput while maintaining a reasonable level of fairness between all the users in the system. A *discrete stochastic dynamic programming model* for the HSDPA downlink scheduler is presented. *Value iteration* is then used to solve for optimal policy. This framework is used to find the optimal scheduling policy for the case of two users sharing the same cell, with 2-state and 3-state channel models. Simulation is used to study the performance of the resulted optimal policy using Round Robin (RR) scheduler as a baseline. The *policy granularity* is introduced to reduce the computational complexity by reducing the action space. The behavior of the value function was observed to characterize the optimal scheduling policy. These observations is then used to develop a *heuristic scheduling policy*. The devised heuristic policy has much less computational complexity which makes it easy to deploy and with only slight reduction in performance compared to the optimal policy according to the simulation results.

Objective

To devise a model and a solution methodology to find the optimal scheduling regime in HSDPA networks, that controls the allocation of the time-code resources.

This policy should have the following properties:
- Fair; Divide the resources fairly between all active users.
- Maximizes the overall cell throughput.
- Provide a high speed and channel aware resources allocation.

Motivation

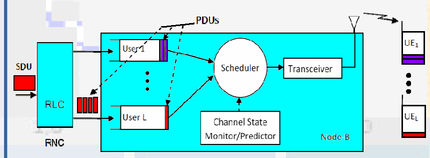
- 3GPP only suggested guidelines for HSDPA downlink scheduler and left the design specifics unspecified.
- This resulted in many different scheduling techniques and implementations most of which are proprietary.
- Most of the available work in scheduler design is based on intuition and creativity of the designers. This approach will result in a suboptimal algorithm at the best, that performs well in some scenarios and poor in the others.

Methodology

- Develop an analytic model for the HSDPA downlink scheduler:
  - MDP-based discrete stochastic dynamic programming model is used to model the system.
  - This Model is a simplifying abstraction of the real scheduler which estimates system behavior under different conditions and describes the role of various system components in these behaviors.
  - Must be solvable
- Define an objective function.
- Value iteration is then used to solve for optimal policy.
- Study the structure of the optimal policy and develop a near-optimal heuristic policy that:
  - Performs close to the optimal policy.
  - Should have much less computation complexity compared to the value iteration used to determine the optimal policy.
  - Can easily be extended to larger queue sizes.

Problem Definition and Conceptualization

The HSDPA downlink channel uses a mix of TDMA and CDMA:
- Time is slotted into fixed length 2 ms TTIs.
- During each TTI, there are 15 available codes that may be allocated to one or more users.



HSDPA Scheduler Model Abstraction (Downlink)

The Model

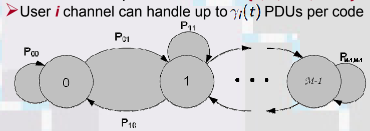
MDP based Model; The HSDPA downlink scheduler is modeled by the 5-tuple $(T, S, A, P_{ss'}(a), R(s,a))$ Where:
- ***T*** is the set of decision epochs,
- ***S*** and ***A*** are the state and action spaces,
- $P_{ss'}(a) = Pr(s(t+1) = s' | s(t) = s, a(s) = a)$ is the state transition probability, and
- ***R(s, a)*** is the immediate reward when at state ***s*** and taking action ***a***.

Basic Assumptions

- There are ***L*** active users in the cell.
- Finite buffer with size ***B*** per user.
- Error free transmission.
- SDUs are segmented by RLC into a fixed number of PDUs (u_i) and delivered to Node-B at the next TTI
- For user $i \in \{1, 2, \ldots, L\}$ and slot $t \in T$, we define:
  - $y_i(t)$ the number of scheduled PDUs,
  - $x_i(t) \in X = \{0, 1, 2, \ldots, B\}$ the queue size,
  - $z_i(t) \in \{0, u_i\}$ the number of arriving PDUs.
- Independent Bernoulli arrivals with parameter q_i.
- Scheduler can assign ***c*** codes chunks at a time, where $c \in \{1, 3, 5, 15\}$.

FSMC State Space

- Channel state of user ***i*** during slot ***t*** is denoted by $\gamma_i(t)$
- Channel state space is the set $\mathrm{M} = \{0, 1, \ldots, M-1\}$.
- User ***i*** channel can handle up to $\gamma_i(t)$ PDUs per code



FSMC Model for HSDPA Downlink Channel

MDP Model Formulation

System State Space

- The system state $s(t) \in S$ is a vector, and is given by

$$s(t) = (x_1(t), x_2(t), \ldots, x_L(t), \gamma_1(t), \gamma_2(t), \ldots, \gamma_L(t))$$

$S = \{\mathcal{X} \times \mathcal{M}\}^L$ is finite; finite buffers and channel states.

Action Set

- The action $a(s) \in A$ is taken when in state ***s*** where $a(s) = (a_1(s), a_2(s), \ldots, a_L(s))$ subject to,

$$\sum_{i=1}^{L} a_i(s) \leq \frac{15}{c}, \quad and \quad a_i(s) \leq \left\lceil \frac{x_i(t)}{\gamma_i(t) c} \right\rceil$$

Reward Function

- ***R(s, a)*** corresponds to the two objectives

$$R(s,a) = \sum_{i=1}^{L} a_i \gamma_i c - \sigma \sum_{i=1}^{L} (B - \bar{x}) \mathbf{1}_{\{x_i = B\}}$$

- The fairness factor (σ) is introduced to reflect the significance of fairness in the optimal policy.

State Equations

The evolution of the queue size (x_i) is given by

$$\begin{aligned} x_i' &= \min\left([x_i - y_i]^+ + z_i', B\right) \\ &= \min\left([x_i - a_i \gamma_i c]^+ + z_i', B\right) \end{aligned}$$

State Transition Probability

We derived the state transition probability and arrived at the following:

$$P_{ss'}(a) = \prod_{i=1}^{L} \left(P_{x_i x_i'}(\gamma_i, a_i) P_{\gamma_i \gamma_i'} \right)$$

Where, $P_{\gamma_i \gamma_i'}$ is the Markov transition probability of the FSMC. Applying total probability law we get

$$P_{x_i x_i'}(\gamma_i, a_i) = \begin{cases} 1 & \text{if } x_i' = x_i = B \ \& \ a_i \gamma_i = 0, \\ q_i & \text{if } x_i' = x_i = B \ \& \ 0 < a_i \gamma_i c \leq u_i, \\ q_i & \text{if } x_i' = B \ \& \ x_i < B \ \& \ W1 \geq B, \\ q_i & \text{if } x_i' < B \ \& \ x_i' = W1, \\ 1 - q_i & \text{if } x_i' < B \ \& \ x_i' = W2, \\ 0 & \text{otherwise.} \end{cases}$$

Where, $W1 = [x_i - a_i \gamma_i c]^+ + u_i$

$W2 = [x_i - a_i \gamma_i c]^+$

The Optimization Criterion

- Infinite horizon expected discounted reward optimality criterion was used. The optimal policy is characterized by

$$V^*(s) = \max_{a \in A} [R(s,a) + \lambda \sum_{s' \subset S} P_{ss'}(a) V^*(s')]$$

Where, $V^*(s) = \sup_\pi V^\pi(s)$ attained when applying the optimal policy π^*.

- ***Value Iteration*** is used to solve the model for the cases ***L = 2, M = 2;*** and ***L = 2, M = 3.***

Heuristic Approach

- Run Value Iteration for small ***B*** to find the optimal policy; then study its structure and behavior.
- Quantify the effect of channel quality and arrival probability variation on the optimal policy structure.
- Use the information to build a heuristic policy that can be extended to larger buffers sizes and more users.

Optimal Policy Structure

- The policy is a ***switch-over*** and can be described as; ***share the codes in proportion to the weighted queue length of the connected users.***
- The weight (w_i) is a function of the difference of the 2 arrival probabilities and that of the channel qualities:

$$\begin{aligned} w_1 &= f([-\Delta P_\gamma]^+, [-\Delta P_z]^+) \\ w_2 &= f([\Delta P_\gamma]^+, [\Delta P_z]^+) \end{aligned}$$

- The intermediate regions has almost a constant width that equals ***2·c***.
- the optimal policy is monotonic.
- a_1 (respectively a_2) is increasing in x_1 (respectively x_2).
- ***f(·)*** is increasing in $|P_\gamma|$ and decreasing in $|P_z|$.

Weight Function Approximation

we approximated w_1 and w_2 as follows

$$\begin{aligned} \hat{w}_1 &= 1 + 1.5[-\Delta P_\gamma]^+ - 0.7[-\Delta P_z]^+ \\ \hat{w}_2 &= 1 + 1.5[\Delta P_\gamma]^+ - 0.7[\Delta P_z]^+ \end{aligned}$$

Heuristic Policy for c = 15

Assign codes to users according to the following rules:
- Rule1: when there is only one connected user then assign all the needed codes to that user,
- Rule2: when both users are not connected (i.e., $\gamma_1 = \gamma_2 = 0$) then no codes will be allocated to any user,
- Rule3: when the two users are connected allocate code chunks according to:

$$a(t) = \begin{cases} (1,0) & \text{if } w_1 x_1 > w_2 x_2, \\ (0,1) & \text{if } w_1 x_1 \leq w_2 x_2 \end{cases}$$

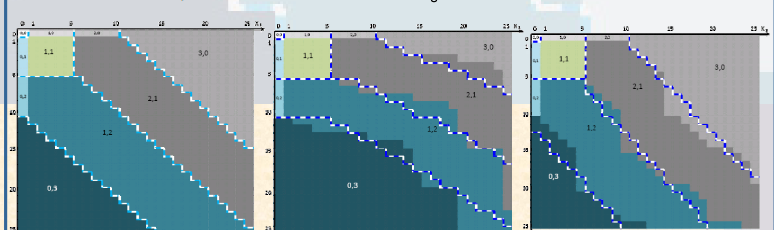
Heuristic Policy for c = 5

The same heuristic policy above will apply here except for Rule3 which will be modified as follows:
- Rule3: when the 2 users are connected, if $x_1 + x_2 < 15$ then allocate codes to the two users in proportion to their queue length, else allocate the code chunks as follows

$$a(t) = \begin{cases} (3,0) & \text{if } w_1 x_1 > w_2 x_2 + 10, \\ (2,1) & \text{if } w_2 x_2 < w_1 x_1 \leq w_2 x_2 + 10, \\ (1,2) & \text{if } w_2 x_2 - 10 \leq w_1 x_1 \leq w_2 x_2, \\ (0,3) & \text{if } w_1 x_1 < w_2 x_2 - 10, \end{cases}$$

- The approach can be extended to any value of ***c***

An example showing the structure of the ***optimal policy*** with the ***heuristic policy*** superimposed on it is given in the figure below*:

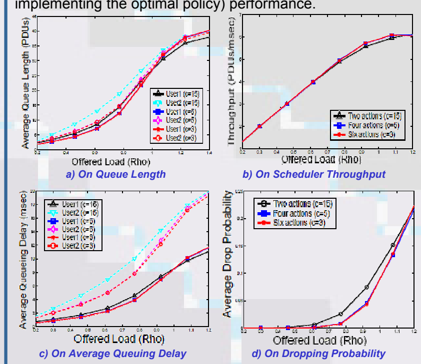


Symmetric users case — $P(\gamma_1=1)=0.8$, $P(\gamma_2=1)=0.5$; $P(z_i=5)=0.5$ — $P(z_1=5)=0.8$, $P(z_2=5)=0.5$; $P(\gamma_i=1)=0.5$

Performance Evaluation

- **Policy Granularity**

Simulation study* have been conducted to evaluate the effect of policy granularity on the HSDPA scheduler (that implementing the optimal policy) performance.



a) On Queue Length — b) On Scheduler Throughput — c) On Average Queuing Delay — d) On Dropping Probability

Fig1: The Effect of Policy Granularity (c=3, 5, or 15)

- **Heuristic Policy Evaluation**

The performance of the devised heuristic policy was studied using simulation, and compared to that of the optimal policy and round robin.

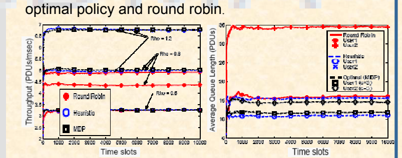
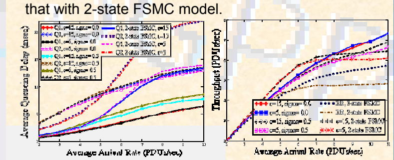


Fig2: Throughput vs. loading — *Fig3: Queue length;* $P(\gamma_1=1)=0.84$, $P(\gamma_2=1)=0.5$, $q_1=0.8$, $q_2=0.5$; $u=10$.

- **3-State FSMC**

The performance of the optimal policy with 3-state FSMC channel model was studied and compared to that with 2-state FSMC model.



a) Average queuing delay vs. load — b) System throughput vs. arrival

Fig4: Optimal policy performance with 3-state FSMC compared to that with 2-state FSMC

Conclusions

- The optimal policy is of a multi-threshold type.
- Finer granularity (down to 5) enhances the performance significantly. However, when c<5, the gain is marginal and does not justify the added complexity.
- The suggested heuristic policy has a reduced constant time complexity (O(1)) as compared to the exponential time complexity needed to compute the optimal policy, and its performance was very closely to the optimal one.
- The optimal policy when using 3-state FSMC model outperformed the one with 2-state model significantly. On the other hand, the value iteration computation complexity was increased by several folds.
- 3-state FSMC model is more accurate representation of the HSDPA downlink channel than the 2-state model.

Future Work

- Extend the heuristic policy to any finite number of users.
- Relax the assumption of error free transmission and extend the model to take into account retransmissions.
- Prove analytically some of the optimal policy and value function characteristics, such as; monotonicity, multi-modularity, and the switch-over behavior.
- Using the developed approach to address scheduling in other wireless systems.
- study the performance of existent schedulers in light of the information we gain from studying the optimal policy structure and behavior.

Web: www.sce.carleton.ca/~hussein

*For complete parameter set and detailed results, please refer to www.sce.carleton.ca/~hussein/TR-optimal%20scheduling.pdf